TACTICAL MANEUVERING
USING IMMUNIZED SEQUENCE SELECTION

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Abstract

This paper describes a tactical maneuvering system that uses an artificial immune system based approach for selecting maneuver sequences. This approach combines the problem solving abilities of genetic algorithms with the memory retention characteristics of an immune system. Of significant importance here is the fact that the tactical maneuvering system can make time-critical decisions to accomplish near-term objectives within a dynamic environment. These objectives can be received from a human operator, autonomous executive, or various flight planning specialists. Simulation tests were performed using a high performance military aircraft model. Results demonstrate the potential of using immunized sequence selection in order to accomplish tactical maneuvering objectives ranging from flying to a location while avoiding unforeseen obstacles, to performing relative positioning in support of air combat maneuvering.

Introduction

Unmanned Aerial Vehicles (UAVs) have been demonstrated as effective platforms for supporting both military and commercial applications. As their role expands, from remotely controlled to semi-autonomous and autonomous operations, challenges are presented which require the development and application of intelligent systems [1]. These systems must be capable of making reliable decisions under varying conditions. As a result, they must incorporate aspects of the experience, reasoning and learning abilities of a pilot. By allowing multiple intelligent systems to work together, through the distribution of roles and responsibilities, the overall level of autonomy of a vehicle can be increased. As a result, human operators can defer the responsibilities of performing and supervising tasks, to focus on managing mission goals and objectives.

In terms of achieving a flight-path goal, a pilot's behavior can be captured through a layered model consisting of discrete-time strategic planning and tactical maneuvering, and continuous-time manual control (Figure 1) [2]. The discrete nature of strategic and tactical behaviors allows for automated decision-making techniques to be applied. Furthermore, since strategic planning decisions are less time-critical, more computationally intensive approaches can be utilized. All of the continuous-time processing elements can be isolated in the automation of manual control.

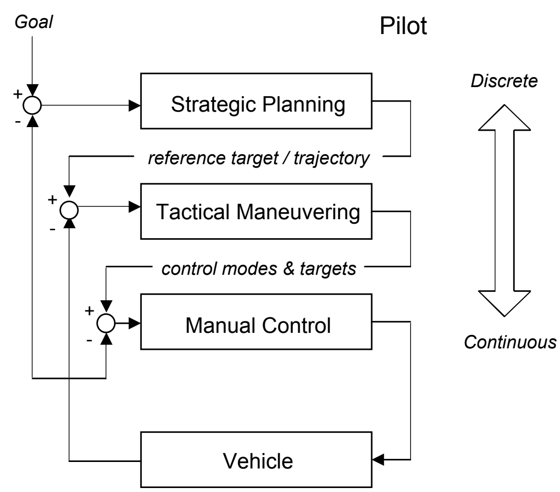


Figure 1. Pilot Behavior Hierarchy

Various flight planning specialists have been developed which enable UAVs to strategically compute their own trajectories in order to achieve mission goals. These trajectories are commonly represented in terms of waypoints and targets. Some of these flight planners, utilizing techniques such as evolutionary algorithms [3] and Voronoi paths [4], are capable of recalculating trajectories in the presence of obstacles or other unforeseen circumstances.

In most applications, lateral and vertical path following control laws are used to automate the task of manual control. In cases where a path is not flyable, interconnecting polynomials (or splines) have been used to smooth out reference trajectories. When guidance corrections do need to be made, specialists such as conventional flight management systems use condition-based control mode transitions. However, since these systems are incapable of "reasoning", there is no guarantee that the necessary corrective actions will be taken for each condition. As a result, path corrections and target adjustments have had to be limited to the strategic level.

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This paper presents a tactical maneuvering system (TMS) that incorporates pilot oriented actions in order to achieve strategically computed objectives (Figure 2). During tactical maneuvering, pilots use their knowledge of aircraft capabilities and near-optimal maneuvering strategies in order to select the necessary actions. These actions can be approximated by piece-wise linear or piece-wise constant commands, and switching between commands [5]. As a result, the interconnection of a finite number of commands can be used to generate motion-based plans that can exploit the full maneuvering capabilities of the aircraft [6]. The TMS incorporates these commands in terms of autopilot modes and targets. The combination of multiple commands forms a maneuver sequence, which represents a near-term aircraft centric trajectory. Once these sequences are generated, they are sent to a specialized autopilot system for execution (Figure 2).

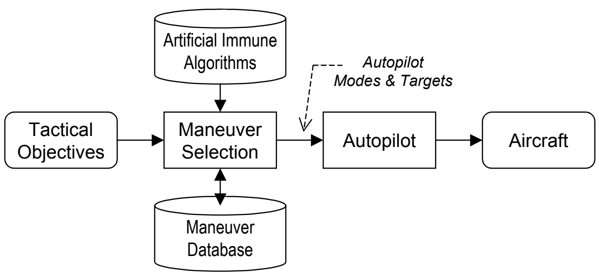


Figure 2. Tactical Maneuvering System

While maneuver sequences can be used to achieve a wide range of tactical objectives, a major challenge is determining how to construct them in a timely fashion. In this innovation, an artificial immune system based approach is used to construct maneuver sequences, by taking advantage of the memory retention and adaptive capabilities of biological immune systems.

A biological immune system can be thought of as a robust adaptive system that is capable of dealing with an enormous variety of disturbances and uncertainties. The artificial immune system combines *a priori* knowledge with the adapting capabilities of a biological immune system to provide a powerful alternative to currently available techniques for pattern recognition, learning and optimization [7]. In this case, the autopilot modes and targets represent the low-level building blocks of the parameterized system. Maneuver sequences representing higher-level building blocks can also be constructed, or learned off-line, to speed-up the search during on-line maneuver selection.

This paper contains an overview of the tactical maneuvering autopilot, the immunized maneuver selection approach, and preliminary test results using a high performance military aircraft simulation.

## Tactical Maneuvering Autopilot

The tactical maneuvering autopilot is based upon a generic neural flight control and autopilot system (Figure 3), which can be applied to a wide range of vehicle classes [8]. However, this autopilot has been enhanced with additional modes and an aggressiveness factor for enabling high performance maneuvers. The command interface has also been modified to process mode and target sequences.

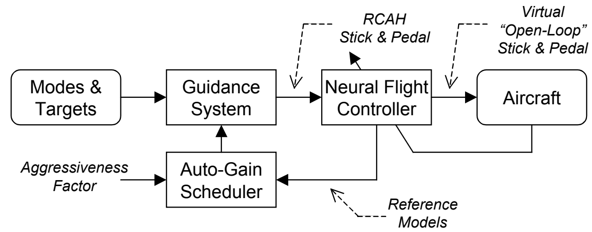


Figure 3. Autopilot System

The direct adaptive tracking neural flight controller provides consistent handling qualities, across flight conditions and for different aircraft configurations. The guidance system takes advantage of the consistent handling qualities in order to achieve deterministic outer-loop performance. Automatic gain-scheduling is performed using frequency separation, based upon an aggressiveness factor and the neural flight controller's specified reference models.

## Neural Flight Controller

The neural flight controller integrates feedback linearization theory with both pre-trained and on-line learning neural networks (Figure 4) [9]. Pre-trained neural networks provide estimates of aerodynamic stability and control characteristics required for model inversion. On-line learning neural networks generate command augmentation signals to compensate for errors in the estimates and from model inversion. Reference models, specifying desired handling qualities, filter rate command attitude hold (RCAH) stick and pedal inputs to generate the corresponding model-following commands.

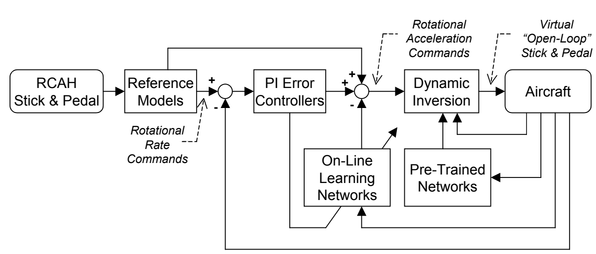


Figure 4. Neural Flight Controller

## Guidance System

The adaptive nature of the neural flight controller enables the guidance system to achieve consistent outer-loop performance without requiring extensive gain-scheduling or explicit system identification. This can represent considerable cost savings, especially in the case of UAVs, during the development of special use vehicles and for accommodating payload reconfigurations.

The system also provides additional potential for adapting to changes in aircraft dynamics under damage or failure conditions. Figure 5 displays a consecutive banking maneuver under a simulated failure, where all flight control surfaces suffered a 70% loss of control power. During the beginning of the maneuver, there was a fair amount of overshoot. This was a result of the integrators in the error controllers having to windup, in order to compensate for the loss of control effectiveness. As the on-line learning neural networks adapted to the error patterns, the integrators were able to unwind. As a result, the amount of overshoot decreased throughout the maneuver.

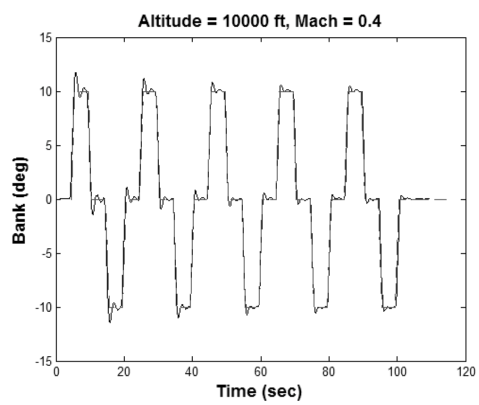


Figure 5. Consecutive Banking Maneuver with 70% Loss of Control Power Failure

Automatic gain-scheduling is performed using frequency separation, based on the natural frequencies of the specified reference models. The aggressiveness factor is used to limit the percentage of allowable RCAH stick and pedal deflections that the guidance system can command. These limits are then propagated throughout the guidance system in the form of computed gains and command limits. In the case of banking maneuvers, the maximum allowable bank angle is computed such that adequate longitudinal stick deflection is available for level-turn compensation.

By adjusting the aggressiveness factor, it is possible to transition the autopilot from a high performance mode for time-critical operations, to a degraded mode for damaged or failure mode operations. Figure 6 displays a 90 degree heading change maneuver for aggressiveness factors of 25% and 75%. During the more aggressive maneuver, the roll rate is higher due to an increased lateral stick deflection limit. However the maximum bank angle is also higher due to an increased longitudinal stick deflection limit, and corresponding pitch rate available for level-turn compensation.

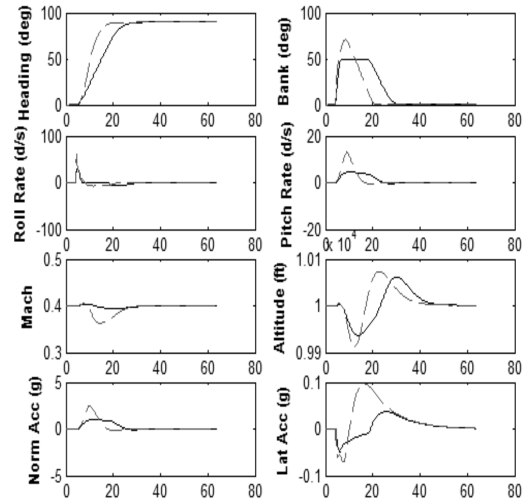


Figure 6. Heading Maneuvers Under Varying Aggressiveness Factors

## Autopilot Commands

Autopilot commands correspond to control modes, which are based upon a conventional autopilot system. However additional body-axis modes have been added to provide the necessary aerobatic maneuvering capability. Each mode corresponds to control laws, which are built upon each other to form a control hierarchy (Figure 7). Each autopilot command consists of a mode identifier and corresponding target.

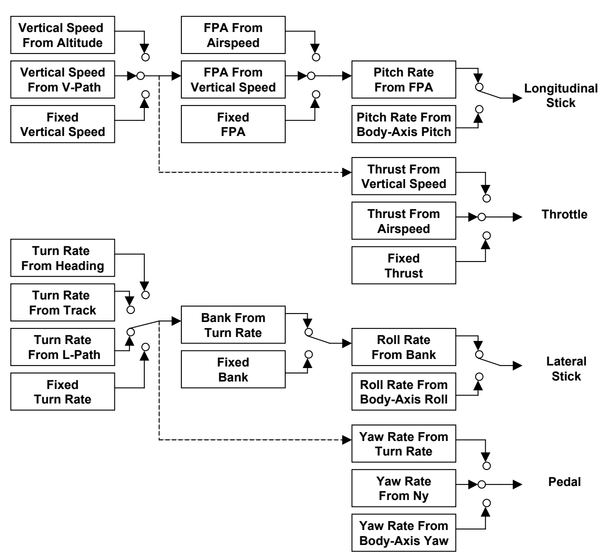


Figure 7. Control Hierarchy

## Maneuver Sequences

A maneuver sequence is composed of one or more autopilot commands, along with scheduling times for command execution. Mode dependent performance models are used to predict the aircraft's state throughout the maneuver. Adjustments can be made to the maneuver sequence, or the performance models, by monitoring the predicted verses actual aircraft state. As a result, it is possible to adapt to small errors in prediction, as well as large changes in aircraft performance resulting from damage or failures.

While maneuver sequences can be generated automatically in order to accommodate situations as they arise, specific sequences can also be constructed to perform common piloting maneuvers. These maneuvers can range from typical maneuvers such as an S-Turn (Figure 8), to aerobatic maneuvers such as a Half-Cuban (Figure 9). Although these maneuvers were constructed manually, using a trial-and-error method, the immunized maneuver selection approach uses a similar method by incorporating predictive performance models.

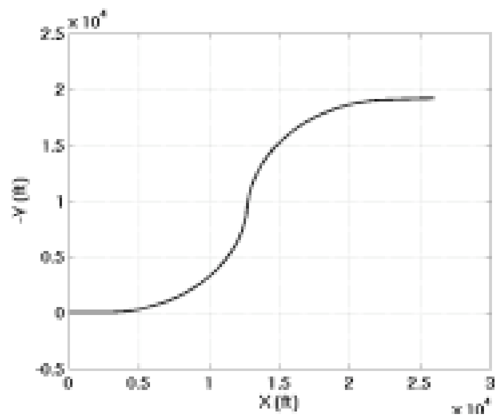


Figure 8. S-Turn Maneuver Sequence

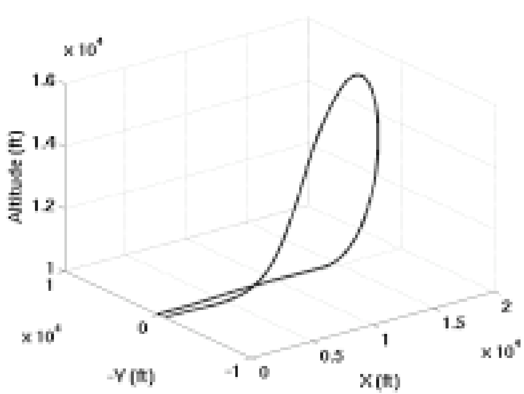


Figure 9. Half-Cuban Maneuver Sequence

## Immunized Maneuver Selection

The immunized maneuver selection (IMS) system uses an artificial immune system (AIS) based approach for selecting maneuver sequences. This approach takes advantage of the memory retention and adaptability characteristics of the biological immune system, in order to solve complex problems in a timely fashion.

In AIS, the search for a solution is modeled after the generation of an immune response wherein the optimal solution is achieved by rapid mutation and recombination of a genetic representation of the solution space. During the generation of the immune response, the system receives a continuous feedback from the antigen-antibody complex resulting in a generation of an increasingly specific antibody response. This represents a learning paradigm that is used in AIS to develop solutions that continually increase in accuracy.

## Immune System Metaphor

The immune system is made up of two major divisions, the innate immune system and the adaptive immune system (Figure 10). The innate immune system is composed of static defenses, such as *skin* and *mucus*, which serve to separate the individual from potential threats. These are supplemented by pre-formed biochemical barriers and other defensive elements, such as *phagocytes*, that are widely distributed in the blood and body tissue. The adaptive response is driven by the presence of the threat. Cells that nullify the threat most effectively receive the strongest signal to replicate.

The basic components of the immune system are white blood cells, or *lymphocytes*. Lymphocytes are produced by the *bone marrow*. Some lymphocytes only live for a few days. The bone marrow is constantly making new cells to replace the old ones in the blood. There are two major classes of lymphocytes: B-cells produced in the bone marrow in the course of so-called clonal selection, and T-cells processed in the *thymus*. B-lymphocytes secrete antibodies and some B-cells survive as memory cells. T-cells are concerned with cellular immunity: they function by interacting with other cells. T-cells divide into helper T-cells, which activate B-cells, and killer T-cells that eliminate intracellular pathogens. Activated B-cells present pieces of the antigens to killer T-cells.

The immune recognition is based on the *complementarity* between the binding region of the receptor and a portion of the antigen called *epitope*. Antibodies do not bind to the whole infectious agent, but rather to one of the many molecules on the agent's surface. This means that different antibodies can recognize a single antigen (Figure 10).

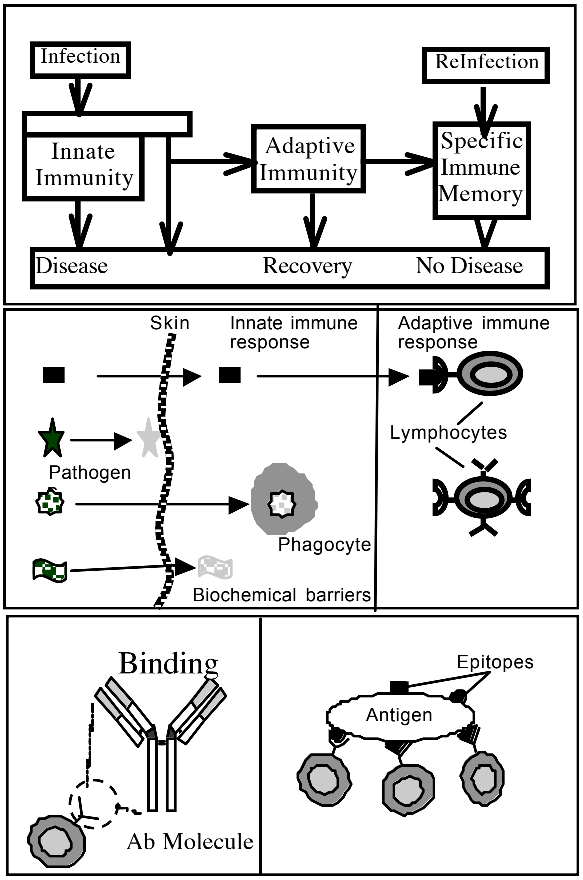


Figure 10. Immune System Functional Flow (Top); Layers of Defense in the Immune System (Middle); Immune Recognition (Bottom)

Figure 11 presents a system-level description of the immune system metaphor. There are several computational models that are based on the principles of immune systems. These are:

- Bone Marrow Models
- Negative-Selection Algorithm
- Clonal Selection Algorithm
- Immune Network Model
- Immunized Computational Systems

The assumption of usability of these models is preceded by the assumption that some understanding of the problem exists. This is akin to the vast source of information available to the immune system. Once this knowledge exists, one can use the immune sub systems individually or in combination (Figure 11). The following sections describe how each of these sub systems is applied for immunized maneuver selection.

Bone Marrow Models

In bone marrow models, gene libraries are used to create antibodies from the bone marrow. The antibody production is through a random concatenation of genes from the gene library. In terms of IMS, the concept of a gene is replaced with the concept of a building block. These building blocks can be thought of as pieces of a puzzle, which must be put together in a specific way to neutralize, remove, or destroy each unique disturbance the system encounters.

A low-level building block (or antibody) is represented by a maneuver. These maneuvers are expressed in terms of autopilot (mode and target) commands and maneuver durations. Maneuver durations are required for constructing a time-based profile.

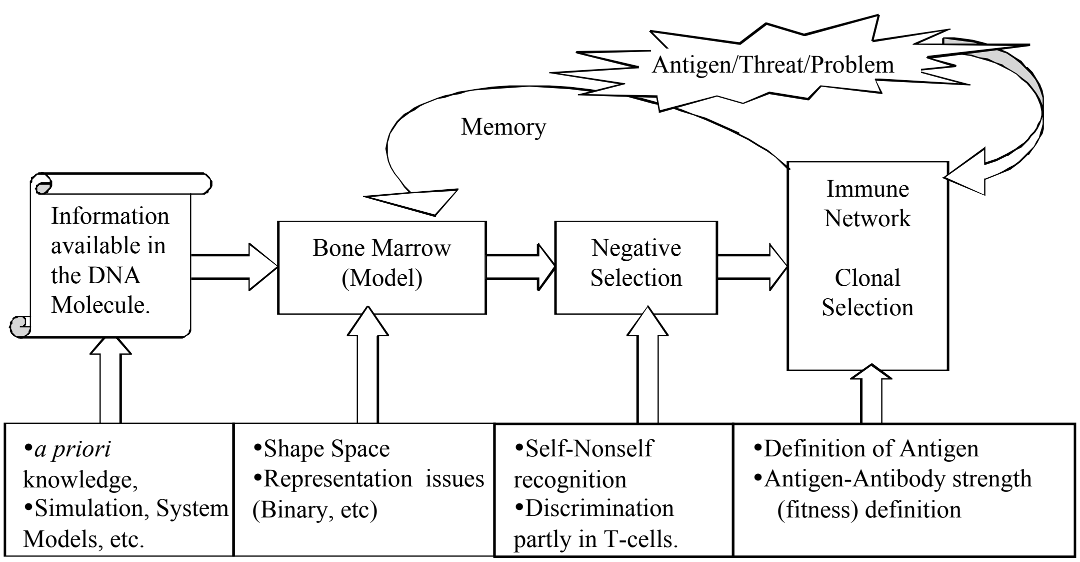


Figure 11. System Level Description of the Immune System Metaphor

Higher-level building blocks that contain multiple maneuvers, in the form of a maneuver sequence, can also be constructed or automatically generated. These building blocks are stored in the maneuver database (or gene library). At a minimum, the initial maneuver database must contain at least one maneuver (or building block) for each available autopilot mode, along with average targets and durations.

Negative-Selection Algorithm

The negative-selection algorithm is based on the principle of self-nonself discrimination in the immune system. This discrimination is achieved in part by T-cells, which have receptors on their surface that detect antigens and then activate the necessary B-cells.

In terms of IMS, various detectors are developed which identify positive characteristics of a tactical objective (or antigen) and characteristics that will be detrimental to the objective. Once these characteristics have been identified, negative selection is applied on the detrimental characteristics. When the appropriate maneuver or maneuver sequence has been selected, the resulting problem-to-solution mapping is stored in a strength matrix. As the connections between tactical objectives and maneuvers grow over time, the likelihood that the necessary maneuvers will be initially selected increases. As a result, the time required for finding a solution will be reduced.

Clonal Selection Algorithm

A distinct difference between biological evolution, and evolution based on the clonal selection principle, is the time scales. The goal of clonal selection is to find the most suitable member of a population in a very short period of time.

The clonal selection algorithm uses selection, cloning, and maturation (or hypermutation) to perform the tasks of discovering and maturing good antibodies from the population of available solutions in an orchestrated fashion. An algorithm is outlined below:

(1) Generate an antibody population either randomly or from a library of available solutions.
(2) Select the *n* best performing antibody population by evaluating a performance index.
(3) Reproduce the *n* best individuals by cloning the population.
(4) Maturate the antibodies by hypermutation.
(5) Re-Select the best performing antibody population.
(6) Stop if antibody generates satisfactory performance, otherwise start over from (1) using probability of mutation.

In terms of IMS, autopilot mode dependent performance models are used to predict the flight path of the aircraft during a maneuver sequence. The predictor takes advantage of the consistent performance, provided by the neural flight controller, to simplify the performance models in terms of command limits and time constants. This allows the prediction to be performed with very little computation, verses having to rely on fast-time simulation at small time steps. The predictor is initialized with the current aircraft states and the aircraft's active flight modes.

The performance index (or cost function) is expressed in terms of weighted parameters, represented by the tactical objectives. These tactical objectives can incorporate both desired and undesired aircraft states, as well as other factors such as time or fuel usage. The desired states indicate what position, speed and direction the aircraft should attempt to achieve at the completion of the maneuver sequence. The undesired states indicate what positions the aircraft should avoid during the maneuver sequence. In cases where obstacles are present, these undesired states can reflect corresponding no-fly zones.

Immune Network Model

In the immune network theory, antibodies recognize both antigens and other antibodies. Antibodies that recognize other antibodies form a network within the immune system. As the antibody matures, it recognizes the antigen with a higher degree of accuracy. Once the antigen is completely removed, the network between like-antibodies helps in keeping the immune system from extinguishing itself. A stable population is maintained as the memory that will be useful for future encounters with similar antigen. Since the learning paradigm in AIS is based on the interaction between populations of antibodies and antigens, this provides a unique way at arriving at self-organizing network structures.

In terms of IMS, successful maneuver sequences are stored in the maneuver database. This represents the equivalent of the network of antibodies (or memory). The connections between antibodies are stored in the form of maneuver sequences. In order to limit the size of the maneuver database, maneuver sequences that are rarely reselected can be deleted over time.

Immunized Computational System

The immunized computation system (ICS) incorporates bone marrow models along with clonal selection to reproduce the robustness and adaptability of a biological immune system.

In terms of IMS, this represents the integration of maneuvers and maneuver sequences (or bone marrow models), tactical objective detectors and strength matrix (or negative-selection algorithm), evolutionary algorithm variant (or clonal selection algorithm), and maneuver database management (or immune network model).

## Simulation Tests

Simulation tests were performed to evaluate the use of IMS in order to accomplish various tactical objectives. Tests were conducted using flight path following and relative positioning oriented objectives, in order to evaluate the potential various applications. These applications could range from flying to a location while avoiding unforeseen obstacles, to performing relative positioning in support of air combat maneuvering.

### Simulator Description

Evaluations were conducted using a high fidelity aerodynamic model of the F-15 ACTIVE aircraft, currently in operation at NASA Dryden (Figure 12). This modified F-15 has been equipped with canards and thrust vectoring nozzles, which can be used to simulate failures in flight. The aircraft is configuration G of the US Air Force's Short takeoff and landing Maneuver Technology Demonstrator (S/MTD) program.

Figure 12. Modified F-15 Aircraft

A Dryden turbulence model was used to provide turbulence RMS and bandwidth values representative of those specified in Military Specifications Mil-Spec-8785 D of April 1989. The Earth atmosphere is based on a 1976 standard atmosphere model.

### Test Description

The IMS algorithms were performed using MATLAB. The generated maneuver sequences were then sent to the flight simulation for execution and evaluation. For these tests, maneuver sequences were not dynamically re-generated during the maneuver. The aircraft was initialized at 5000 feet with a true heading of 0 degrees. Initial airspeeds varied from 250 feet/sec to 450 feet/sec. All tests were performed in light turbulence.

The maneuver database that was used contained several maneuvers (or low-level building blocks) for each autopilot mode. The maneuver database did not contain pre-generated maneuver sequences (or high-level building blocks). Also, the size of the maneuver sequence was fixed to a specific number of building blocks, during each test, and varied as an experimental condition. Since tests were not performed using consecutive tactical objectives, successful maneuver sequences were not stored back into the maneuver database.

For all tactical objectives, cost function weights were either set to 0 or 1. The probability matrix was also configured with elements of 0 or 1, so that a set of typical maneuvers would be selected into the initial population. However additional randomly selected maneuvers were also incorporated into the initial population to provide diversity.

### Single Maneuver Tests

Single maneuver tests were performed in order to determine if IMS was capable of selecting a valid maneuver in order to achieve a simple objective. Once the maneuver was selected, the system also had to chose an appropriate target.

Figure 13 shows a single heading maneuver that was selected in order to fly over a waypoint with a longitudinal offset of 2000 feet, and a lateral offset of 1000 feet. In this case, IMS chose a heading maneuver in order to make the necessary lateral correction. A heading change of 63 degrees (to the right) was also chosen in order to intercept the target.

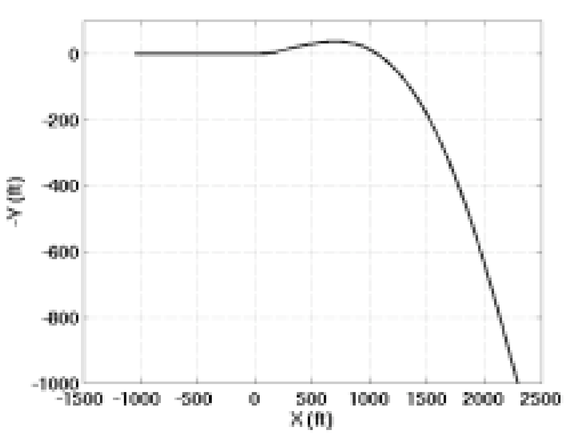


Figure 13. Single Heading Maneuver

While the aircraft was directed towards the target, it overshot the target by approximately 300 feet. This was primarily due to an initial sideslip, which was not reflected in the heading performance model. While gross acquisition of the target was achieved, fine-tracking performance was not.

Optional methods for improving fine-tracking accuracy include (1) dynamically re-computing (or modifying) active maneuvers, (2) the use of higher fidelity fast-time models, (3) the incorporation of an initial compensation factor, and (4) the addition of a "direct-to" control law. While the first two methods would increase computational requirements, the last method has the potential of actually reducing the necessary level of processing. The introduction of specialized control modes can reduce the number of maneuvers required to perform a specialized action.

Double Maneuver Tests

Double maneuver tests were performed in order to determine if IMS was capable of connecting multiple maneuvers together to form a maneuver sequence. Not only did the system have to select the necessary maneuvers and targets, but it also had to determine the proper order as well as when to schedule the second maneuver.

Figure 14 shows a double heading maneuver that was selected in order to intercept a waypoint with a longitudinal offset of 4000 feet, a lateral offset of 1500 feet. However, the aircraft also had to cross the waypoint when flying a heading of 0 degrees. In this case, IMS chose two heading maneuvers that approximated a pseudo S-Turn maneuver sequence. A heading change of 51.8 degrees (to the right) was chosen for the first command, followed by a second heading change of –53.8 degrees (to the left). The second command was initiated 7.9 seconds after the first command was issued.

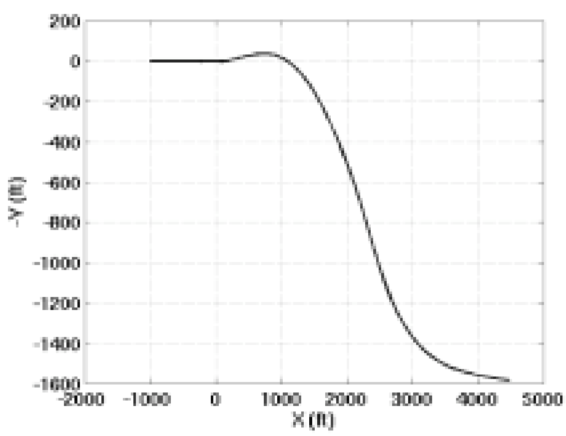


Figure 14. Double Heading Maneuvers

This test achieved results that were similar to the single heading maneuver, in terms of gross acquisition and fine-tracking accuracy. Since the same initial error was introduced, the double heading maneuver also overshot the intended waypoint before capturing the commanded intercept. However, IMS was able to successfully construct a maneuver sequence using two consecutive lateral maneuvers.

Triple Maneuver Tests

Triple maneuver tests were performed in order to determine if IMS was capable of combining multiple lateral and vertical maneuvers into a maneuver sequence. In this case, the scheduling of maneuvers could have an affect on longitudinal and lateral coupling. The distance of the lateral track will also have a direct affect on time available for completion of the vertical maneuver.

Figure 15 shows a triple coupled maneuver that was selected in order to intercept a waypoint with a longitudinal offset of 5000 feet, a lateral offset of 5000 feet, and an intercept heading of 0 degrees. However, in this case, the aircraft was also supposed to climb 2000 feet before reaching the waypoint.

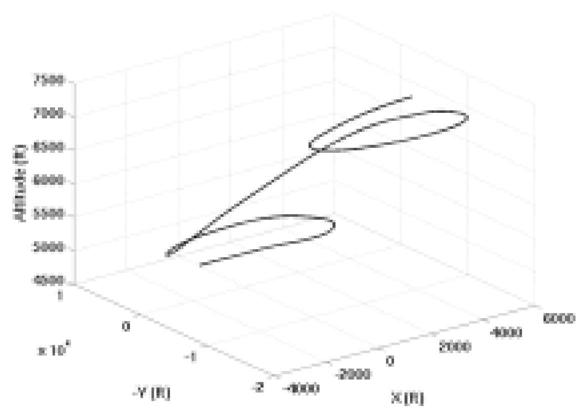


Figure 15. Triple Coupled Maneuver

While the unexpected result did satisfy the objective, the path that the aircraft chose was extraordinarily long. Although a path length penalty was not reflected in the cost function, one would expect that a simpler "Climbing S-Turn" maneuver sequence should have been easier to construct. However, it turns out that IMS was not taking advantage of the simultaneous scheduling of lateral and vertical maneuvers. As a result, the "Climbing S-Turn" could not be generated. While this issue can be resolved, it is interesting to note that a valid solution was found, even in the presence of these additional constraints.

## Conclusions

This paper presented a tactical maneuvering system that integrates advanced flight control and autopilot techniques with an IMS system, which uses an AIS-based approach for maneuver sequence selection. AIS characteristics, such as adaptability and inherent memory management, make it possible to create new solutions in a short period of time. As a result, IMS has the potential for solving the complex and time-critical problems inherent in tactical maneuvering.

The tactical autopilot system was shown to be capable of high performance aerobatic maneuvers, while also maintaining the ability of flying under degraded modes. However, perhaps one of the tactical autopilot's greatest benefits is the deterministic behavior it provides. This is especially important since IMS relies on predictive performance models for clonal selection.

Preliminary results demonstrate that IMS can successfully select multiple maneuvers and construct them into a maneuver sequence in order to achieve a tactical objective. However, more work is needed in certain core areas, which include:

- Model Prediction – to incorporate rate limits and other constraints associated with the operating envelope, and to further reduce the computation required for model prediction.

- Maneuver Sequence Scheduling – to enable simultaneous and overlapping maneuvers, and to improve the application of delay intervals between maneuvers.

- Clonal Selection Algorithm – to improve the efficiency of the evolutionary process through manipulation of population size, number of generations, and other contributing factors.

- Negative-Selection Algorithm – to enhance tactical objective characteristic classifications, and enable dynamic antigen-antibody strength matrix adaptation.

- Maneuver Database Management – to enable introduction of both off-line and on-line generated maneuver sequences into the database, and provide guidelines for removal.

As these technologies mature, assessments can be made in regards to the potential of using IMS for various other applications. However, some applications requiring higher-levels of autonomy may also require integration with other intelligent systems, such as health management, situational awareness, planners and schedulers.

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